Southern Illinois University at Carbondale
COLLEGE OF ENGINEERING
Carbondale, Illinois 62901-6603

SIU

Final Technical Report

Contract- N00014-94-1-0736

Title: Distributed Sensor Fusion
Based on Statistical Inference

PI: Ramanarayanan Viswanathan

Department of Electrical Engineering

Final Technical Report

Contract- N00014-94-1-0736

Title: Distributed Sensor Fusion Based on Statistical Inference

PI: Ramanarayanan Viswanathan

Final Report on the Contract- N00014-94-1-0736

Title **Distributed Sensor Fusion Based on Statistical Inference**

PI **Ramanarayanan Viswanathan**

During the contract period we have addressed several issues related to distributed detection and estimation problems. Specifically, we considered posterior robustness of decentralized detection problems, distributed constant false alarm rate (CFAR)detection, computation of loss associated with distributed detection, distributed location parameter estimation and rank based test for M-ary detection. Results obtained from this study are briefly summarized.

1. Posterior Robustness of Decentralized Tests

We considered the posterior robustness of a decentralized detection problem where the prior density is not completely known, but is assumed to belong to an ε - contamination class[1]. The expressions for the infimum and the supremum of, the posterior probability that the parameter under question is in a given region, as the prior varies over the ε - contamination class, are derived. Numerical results were obtained for representative cases of (i) exponentially distributed observation and an exponentially distributed nominal prior and (ii) normally distributed observation and a normally distributed prior. Asymptotic (as number of sensors tends to a large value) results are also obtained for two situations pertaining to a central fusion rule. For the decentralized case, it is assumed that the sensors send binary information to the fusion center where a k-out-of-n counting rule is employed. In general, the results illustrate the degree of robustness achieved with quantized observations as compared to unquantized observations. The AND, OR and the majority logic rule all perform sub-optimally as compared to the central fusion scheme. The sub-optimality does not vanish even if one has a large collection of sensors. The derivations also reveal certain monotonicity property of AND and OR rules[1]. It is also shown that given the observation density, the contamination proportion and the nominal prior, the value of k in the k-out-of-n fusion rule that gives the best performance in a worst case sense, can be found.

2. Distributed CFAR Detection

We developed a new CFAR test using distributed sensors for detecting radar targets[2]. Unlike the previous distributed CFAR detectors which combine the local detectors' decisions by the AND or the OR combining rule at the fusion center[3], in the new scheme, each sensor transmits its test sample and a designated order statistic of its surrounding observations to the fusion center. At the fusion center, the sum of the test cells' samples is compared to a constant multiplied by a function of the order statistics. Two functions, namely the maximum(MOS), and the minimum (mOS), were considered. The numerical results for Rayleigh target in Rayleigh clutter indicate that the MOS scheme performs considerably better than the OS-CFAR detector with the AND or the OR rule[2]. The MOS scheme also performs nearly as good as a central OS-CFAR detector

that uses all the reference samples from both the sensors. However, the above formulation has assumed that the test cells of different sensors all have identical noise(clutter), and that if a target is present in the surveillance regions, all the test cells have statistically identical target returns. What would happen if this assumption is violated? Our evaluation shows that the performance of MOS test degrades to some extent, depending on the statistical dissimilarities between the returns in the test cells of different sensors[4,5].

In order to address dissimilar clutter power situation, we formulated another distributed CFAR scheme called the normalized test statistic, where the data from the test cells of each sensor are weighted and then added to form the test statistic. In the normalized statistic, the weighting coefficient of a sensor is determined by an order statistic of the cells surrounding the test cell. For a two sensor network, the performance of this test is compared with that of the standard OR rule[4,5]. In both homogeneous background and interfering target situations, the probability of detection of normalized test statistic is only slightly larger than that of the OR rule. However, considering that the normalized test statistic requires each sensor to send two real numbers, a test cell sample and an order statistic, whereas the OR rule requires each sensor to send only a bit decision to the fusion center, it can be said that the OR rule provides a competitive and acceptable performance at a low cost. The only drawback of both these tests is the large increase in false alarm rate during a clutter transition in the middle of the reference window. If the homogeneous background noise powers in all the sensors are nearly identical, then the MOS test provides a much better performance than the OR rule[2]. However, the MOS test is seen very sensitive to the sensor to sensor variations in clutter powers.

The author has written a comprehensive review of radar CFAR tests that are based on order statistics[6].

3. <u>Performance Loss Computation</u>

An important question in a distributed signal detection system (DSD) is the loss associated with the system as compared to a centralized detection system. Our approach quantifies the loss associated with a DSD system by providing an easily computable probability of error expression[7]. The problem formulation assumes that the sensor observations are *i.i.d* conditioned on the signal or no signal hypothesis. It is also assumed that k out of n sensors send only quantized (binary) information to the fusion center whereas the rest of the sensors send their observations (unquantized) to the fusion center. The progressive changes of probability of error of a likelihood ratio test at the fusion center as k increases from 0 to n show the effect of quantization loss associated with a DSD system. When the density belongs to an exponential family of distributions, we obtain easily computable error expressions. Results show that for normal and gamma (with a large shape parameter) densities, the loss due to quantization is more significant than for exponential density.

4. <u>Distributed Location Parameter Estimation</u>

We considered the estimation of the location parameter of a density function using distributed sensor data[8]. The data from the sensors are assumed to be statistically independent. The estimation problem becomes trivial if a (nontrivial) sufficient statistic for the parameter exists because it is known that a global sufficient statistic can be obtained as a function of the local (per sensor) sufficient statistics[9]. Hence, we considered as

examples the Cauchy and the Laplace densities- the density functions that do not possess sufficient statistics. Basically the Mean Square Error (MSE) has been used as the performance criterion and the decentralized schemes considered are (1) weighted combination of local estimates (2) an order statistic of the local estimates (3) weighted combination of local estimates, when the sample sizes at the local sensors are different (4) the central median estimator (5) the central Best Linear Unbiased estimator(BLUE). For all the schemes, a local estimate is taken as the median of the samples available at that local sensor. This choice has been made because it is robust and it is the MLE for the Laplace distribution. For scheme (1), the optimal weights are all equal, if the sample sizes at the sensors are all the same. That is, averaging will be the best linear MSE estimator. As expected, the central BLUE has the smallest MSE among the various schemes considered. An interesting result is that for Laplace density, scheme (1) has a lower MSE than scheme (2), for certain values of the number of samples per sensor and the number of sensors. That is, a global estimate which is the average of the medians has a lower MSE than the median of the medians. Another result pertaining to the average of local median estimator is that, assigning different samples to different sensors, in general, does not provide any smaller MSE than that obtained with equal sample size for all the sensors. Two cases of large sample situation were also considered. These were (i) finite number of samples per sensor and infinite number of sensors and (ii) infinite number of samples per sensor and a finite number of sensors.

5. Rank Based Tests for M-ary Detection

We considered a rank order based test for a general M-ary communication problem, which can be stated as follows: Given M groups of L samples each, the problem is to identify which unique group of L samples have come from the signal hypothesis. The optimal likelihood ratio test that minimizes the probability of incorrect classification can be constructed if the joint distribution of these ML samples is completely known. However, in many cases, the distribution is either unknown or only known partially. Therefore, suboptimal tests, such as tests based on rank orders, can be considered. By considering the observations as a matrix of M rows with L columns, a rank matrix is created by rank ordering these observations and then replacing the samples with their corresponding ranks. Then a *Rank Sum Test* declares the row with the maximum rank sum as the row corresponding to the signal hypothesis. Since ranking ML samples might take considerable amount of time, a *Reduced Rank Sum Test* (RRST)rank orders the samples in each column separately into values of 1 through M, and then picks the row with the maximum rank sum. A variation of the RRST is to create a value matrix where the (i,j) element of the value matrix is either equal to the (i,j) element of the rank matrix, if the rank exceeds a threshold t, or is equal to zero. The *Modified Rank Test* (MRT) then picks the row with the maximum sum of values. If $t=M$, the MRT retains only the maximum rank of M in each column and assigns zero values to the others. In other words, independently for each column, the row with the largest rank is decided as the signal row. Therefore, for $t=M$, MRT can be thought of as a majority logic combining of the decisions made in each column. For other values of t, MRT can be thought of as combining decisions, when decisions are presented with confidence weights. We examined the efficiency of MRT for different signal detection scenarios. The results show that for detection in a heavy tailed noise such as Laplace, the MRT with t less than M is more

efficient than the RRST. Considerable improvement in efficiency above that of majority logic ($t=M$) can be obtained by using a value of M-1 or M-2 for t[10].

The results indicate that it may be worth examining the performance of MRT and determine (i) its behavior in combating partial band jamming noise in FH-MFSK systems and (ii) its usefulness in combining antenna array signals in IS-95 DS-CDMA mobile systems.

References

1. C.H. Gowda and R. Viswanathan, "Posterior robustness of decentralized tests with ε -contamination prior," *IEEE Transactions on Information Theory*, July 1995, pp.1164-1169.
2. H. Amirmehrabi and R. Viswanathan, "A New Distributed Constant False Alarm Rate Detector," *IEEE Transactions on Aerospace and Electronic Systems*, Jan. 1997, pp. 85-97.
3. M. Barkat and P.K. Varshney, "Decentralized CFAR Signal Detection," *IEEE Transactions on Aerospace and Electronic Systems*, Mar. 1989, pp. 141-148.
4. C.H. Gowda, M.K. Uner, P.K. Varshney and R. Viswanathan, "Distributed CFAR target detection," Proceedings of workshop on Foundations of Information/Decision Fusion, Washington D.C., Aug. 1996, pp. 79-84. Also to appear in Journal of Franklin institute, 1997.
5. C.H. Gowda and R. Viswanathan, "Performance of Distributed CFAR Tests in Nonhomogeneous Background," Proceedings of National Radar Conference, 1997, pp. 36-41.
6. R. Viswanathan, "Order Statistics Application to CFAR Radar Target Detection," in *Handbook of Statistics, Vol. 16- Order Statistics and Their Applications*, N. Balakrishnan and C.R. Rao Eds., North-Holland Publishers, 1997.
7. H. Amirmehrabi and R. Viswanathan, "Performance Loss Computation in Distributed Detection," Summary in *Proceedings of International Symposium on Information Theory*, Whistler, B.C., Canada, Sept. 1995, pp.295.
8. M. Su, J. Cheng and R. Viswanathan, Distributed Estimation of Location Parameter of Two Example densities," Proceedings of Allerton Conference on Communications, Control and Computing, Urbana-Champaign, Oct. 1996, pp. 1009-1018.
9. R. Viswanathan, "A Note on Distributed Estimation and Sufficiency," IEEE Transactions on Information Theory, Sep. 1994, pp. 1765-1767.
10. V. Annampedu and R. Viswanathan, "A Rank Based Test for M-ary Detection," presented at Conference on Information Sciences and Systems, Johns Hopkins University, March 1997, to be included in the conference proceedings.

Publications

Journals

1. R. Viswanathan and P.K. Varshney, "Distributed Detection With Multiple Sensors: Part I- Fundamentals," *Proceedings of IEEE*, Jan. 1997, pp.54-63.
2. C.H. Gowda, M.K. Uner, P.K. Varshney and R. Viswanathan, "Distributed CFAR target detection," to appear in Journal of Franklin institute, 1997.
3. H. Amirmehrabi and R. Viswanathan, "A New Distributed Constant False Alarm Rate Detector," *IEEE Transactions on Aerospace and Electronic Systems*, Jan. 1997, pp. 85-97.
4. C.H. Gowda and R. Viswanathan, "Posterior robustness of decentralized tests with ε -contamination prior," *IEEE Transactions on Information Theory*, July 1995, pp.1164-1169.
5. R. Viswanathan, "A Note on Distributed Estimation and Sufficiency," IEEE Transactions on Information Theory, Sep. 1994, pp. 1765-1767.
6. V. Annampedu and R. Viswanathan, "A Rank Based Test for M-ary Detection," submitted to *IEEE Transactions on Information Theory*, March 1997.

Book Chapter

1. R. Viswanathan, "Order Statistics Application to CFAR Radar Target Detection," in *Handbook of Statistics, Vol. 16- Order Statistics and Their Applications*, N. Balakrishnan and C.R. Rao Eds., North-Holland Publishers, 1997.

Conference Proceedings

1. C.H. Gowda and R. Viswanathan, "Performance of Distributed CFAR Tests in Nonhomogeneous Background," Proceedings of National Radar Conference, 1997, pp. 36-41.
2. V. Annampedu and R. Viswanathan, "A Rank Based Test for M-ary Detection," presented at Conference on Information Sciences and Systems, Johns Hopkins University, March 1997, to be included in the conference proceedings.
3. M. Su, J. Cheng and R. Viswanathan, Distributed Estimation of Location Parameter of Two Example densities," Proceedings of Allerton Conference on Communications, Control and Computing, Urbana-Champaign, Oct. 1996, pp. 1009-1018.
4. H. Amirmehrabi and R. Viswanathan, "Performance Loss Computation in Distributed Detection," Summary in *Proceedings of International Symposium on Information Theory*, Whistler, B.C., Canada, Sept. 1995, pp.295.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*

2. REPORT DATE
6-24-97

3. REPORT TYPE AND DATES COVERED
Final Report 6-1-94 through 5-31-97

4. TITLE AND SUBTITLE
Distributed Sensor Fusion Based on Statistical Inference

5. FUNDING NUMBERS
Contract
N 00014-94-1-0736

6. AUTHOR(S)
Ramanarayanan Viswanathan

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Electrical Engineering Department
Southern Illinois University at Carbondale
Carbondale, IL 62901-6603

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Office of Naval Research
Ballston Tower One
800 North Quincy Street
Arlington, VA 22217-5660

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*

We addressed several issues related to distributed detection and estimation problems. We examined the posterior robustness of decentralized detection schemes when the prior density is not completely known. The results indicate the degree of robustness that could be achieved with quantized observations. We developed a new CFAR test using distributed sensors for detecting radar targets. The numerical results for Rayleigh target in Rayleigh clutter indicate that, undercertain assumptions, the newly developed MOS test performs considerably better than the OS-CFAR detector with the AND or the OR fusion rule. As shown here, the performance loss associated with a distributed detection scheme can be assessed using an easily computable probability of error expression, when the density of sensor observation belongs to the exponential family. In distributed parameter estimation we numerically evaluated the mean squared error performances of several estimation schemes for two example situations. Fianlly, we have analyzed a rank based test for M-ary detection problems. The results show that the new modified rank test can provide performance gain in detecting signals in non-Gaussian noise.

14. SUBJECT TERMS
Posterior Robustness, Distributed Detection, Estimation, CFAR Tests, Rank Tests

15. NUMBER OF PAGES
6

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT

18. SECURITY CLASSIFICATION OF THIS PAGE

19. SECURITY CLASSIFICATION OF ABSTRACT

20. LIMITATION OF ABSTRACT

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. Z39-18
298-102